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Abstract

This paper investigates whether the daily stock returns of the Polish, Czech and Hungarian stock markets are covariance stationary. Using the Pagan – Schwert (1990) and Loretan – Phillips (1994) testing procedures, we show that contrary to the widely accepted assumption of covariance stationarity, the stock returns in Central and Eastern European (CEE) stock markets do not appear to be covariance stationary. Our results further suggest that the occurrence of unconditional volatility shifts appears to be synchronized across stocks.

Keywords: covariance stationarity, unconditional volatility, volatility regimes, CEE stock markets

JEL Classification: C10, G10, G15

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Introduction

We can consider a stochastic process $\{Y_t\}_{-\infty}^{\infty}$ to be covariance stationary if for all t and j, $E[Y_t] = \mu$, $|\mu| < \infty$, $\text{cov}(Y_t, Y_{t-j}) = \gamma_{YY}(j)$, $|\gamma_{YY}(j)| < \infty$. Covariance stationarity of a stochastic process is one of the most widely used assumptions in empirical finance. Policy recommendations are often based on vector autoregression models, estimated with (assumed) covariance-stationary variables. More specifically, when the unconditional volatility changes, calculating the autocorrelation function over the whole sample is meaningless. Standard generalized autoregressive conditional heteroskedasticity (GARCH) or other stochastic volatility models also assume covariance stationarity of Y_t (integrated GARCH is one of the exceptions). Furthermore, if the first two moments are not fixed, forecasting possibilities are limited (e.g., in VaR models) and parameter estimates may be inconsistent.

Unit-root tests are a specific class of tests, which are used to discriminate between a mean stationary (or trend stationary) and a random walk process. The variations of the ADF-GLS test (see, Elliott *et al.*, 1996; Ng – Perron, 2001; Perron – Qu, 2007) and the KPSS test (see, Kwiatkowski *et al.*, 1992; Hobijn *et al.*, 2004) are most likely the most popular among unit-root/stationarity tests. Even if Y_t is considered mean stationary, its unconditional variance may be time dependent, thus invalidating the covariance stationarity assumption. One well-known consequence of this time-dependency of the unconditional variance is the overestimation of the persistence of conditional volatility in the ARMA-GARCH model of stock returns if shifts in the unconditional volatility are not considered (e.g., Aggarwal *et al.*, 1999; Ewing – Malik, 2010; Výrost *et al.*, 2011). It appears that the assumption of covariance stationarity is of great importance. If possible, one should consider formal tests to evaluate whether the data support the covariance stationarity assumption.

Pagan – Schwert (1990) proposed three tests to assess the equality of variances. The authors found convincing evidence that during the period from January 1834 to December 1987, the monthly stock return series exhibited covariance nonstationarity. Loretan – Phillips (1994) showed that if the fourth moments are not finite, one needs to adjust critical values of the Pagan – Schwert (1990) test. Loretan – Phillips (1994) rejected the null of covariance stationarity for all seven series: five daily USD exchange rate return series (with France, Germany, Japan, Switzerland, United Kingdom over the period from December 1978 to January 1991) and two stock market return series (monthly returns as in Pagan – Schwert, 1990; and daily S&P index returns from July 1992 to December 1987). Omran – McKenzie (1999) and Ho – Wan (2002) extended the empirical analysis first by testing for variance constancy and second by adjusting the original series for exogenously defined volatility shifts. Omran – McKenzie (1999) found that during the period from 2 January 1970 to 17 October 1997, the daily FTSE All-share stock market index returns were not covariance stationary. The authors subsequently confirmed that volatility shifts occurred during the oil crisis of 1973 – 1974 and the market crash in October 1987. When these shifts in volatility were removed from the original series, the Pagan – Schwert (1990) and Loretan – Phillips (1994) statistics were insignificant. A similar approach was implemented in Ho – Wan (2002). The authors' four samples of daily stock market index returns covered the period from 1990 to 2000 (sample sizes of Australian All Ordinaries, Hang Seng, Singapore Straits Times, and Dow Jones Industrial Average were unequal; see Ho – Wan, 2002 for a detailed description). Covariance stationarity was not rejected only for the Australian All Ordinaries index. Ho – Wan (2002) considered the impact of two shifts in volatility (exogenously determined). One shift corresponded to the Asian financial crisis in 1997, and the other shift corresponded to the Russian and Latin American currency crisis of 1998. In the adjusted series, where the effects of possible shifts in volatility were removed, covariance stationarity was not rejected for the Hang Seng and Singapore Straits Times indices.

In this paper, we investigate whether the daily stock returns at the Prague, Budapest and Warsaw stock exchanges during the period from 1 December 1998 to 17 October 2012 may be regarded as covariance stationary. The empirical findings suggest that stock returns are not covariance stationary. Moreover, as we identified possible shifts in the unconditional volatility, we observed that volatility shifts appear to be synchronized, suggesting that common factors are responsible for the break of covariance stationarity.

The rest of the paper is organized as follows. Section 1 describes the data, while in Section 2, the tests employed are briefly discussed. Empirical results are presented and discussed in Section 3, and the last section concludes.

1. Data

The data consist of daily adjusted closing prices (P_t) for stocks that as of 30 November 2012 were constituents of the WIG-20, PX and BUX stock market indices and that, at the same time, had been traded throughout the period from 1 December 1998 to 17 October 2012. The data were obtained from Datastream. Our final sample included 16 stocks, each having

$T = 3621$ observations of daily stock returns.[1] The following tickers of the stocks selected in our sample are included: PM, CEZ, KB, UNI, O2 from PX index, EGIS, PAE, REG, OTP, MOL, MTK from the BUX index and BRE, HAND, KGHM, BPOL, and TEL from the WIG-20 index.

The stock returns $r_t = \ln(P_t) - \ln(P_{t-1})$ were demeaned and fitted with an autoregressive model estimated via OLS to obtain the residuals ε_t (excess returns). The order of the AR model (starting from 0, 1, ...) was determined by the insignificance of the Ljung – Box test of the serial dependence of residuals (for lags 1 to 12 with a significance level $\alpha = 0.10$).

2. Methodology

In general, there is little doubt about the mean stationarity of stock returns r_t. In contrast, the liquidity and volume is usually lower in CEE stock markets than in more developed stock markets. Therefore, we decided to conduct a formal test of mean stationarity in the first step of our analysis. Next, we applied the Pagan – Schwert (1990), Loretan – Phillips (1994) covariance stationarity test to residuals ε_t.

The mean stationarity of r_t was tested by using the ADF-GLS test of Elliott *et al*. (1996) and the KPSS test of Kwiatkowski *et al*. (1992). In the ADF-GLS testing procedure we test the null hypothesis that $\phi = 0$ against $\phi < 0$ in the following auxiliary regression:

$$\Delta\tilde{\varepsilon}_t = \phi\tilde{\varepsilon}_{t-1} + \sum_{i=1}^{k}\delta_i\Delta\tilde{\varepsilon}_{t-i} + u_t \qquad (1)$$

where $k > 0$ is the number of the lagged differences of the GLS detrended ε_t (note that we use only models with a constant). The number of the lagged differences in *(1)* is determined from $k = 1, 2, ..., k_{\max}$, where $k_{\max} = \text{int}[12(T/100)^{0.25}]$ (Schwert, 1989). The optimum number of lagged differences k_{opt} can be chosen according to at least four rules. First, we considered k_{opt} for which the null of no autocorrelation in u_t was not rejected using the Ljung – Box test calculated from one to $0.05T$ lags at significance level $\alpha = 0.05$. Second, we employed the sequential top-down approach as used by Ng – Perron (1995). We start by estimating *(1)* with $k = k_{\max}$. If the δ_k coefficient is not significant at $\alpha = 0.1$, we re-estimate *(1)* with $k = k_{\max} - 1$. This process is repeated until δ_k is significant or $k = 1$. Third, we determined k according to the Modified Akaike Information Criterion (MAIC), as used by Ng – Perron (2001). Finally, we determined k according to the MAIC applied to a model

[1] One stock from WIG-20 was excluded for having periods of no volatility (i.e., no real price changes).

specified similarly as *(1)*; however, instead of GLS detrended data, OLS detrended data were used for the determination of the MAIC (see, Perron – Qu, 2007). These test statistics are denoted as $\tau_{\mu,u}^{\text{GLS}}$, $\tau_{\mu,s}^{\text{GLS}}$, $\tau_{\mu,m}^{\text{GLS}}$, and $\tau_{\mu,O}^{\text{GLS}}$.

The KPSS test of Kwiatkowski *et al*. (1992) of the null of mean stationarity is based on the following test statistics:

$$w = \frac{\sum_{t}^{T}\left(\sum_{i}^{t}\hat{o}_i\right)^2}{T^2\hat{\sigma}^2} \tag{2}$$

$$\varepsilon_t = \alpha + d\sum_{i=1}^{t} w_i + o_t \tag{3}$$

where w_i and o_i are assumed to be covariance stationary processes, and $d = \{0, 1\}$. For $d = 1$, ε_t is a unit-root process, while for $d = 0$ it is regarded to be mean stationary. The estimate of the long run variance σ^2 of o_i is denoted as $\hat{\sigma}^2$, and we used a nonparametric estimation in the following form:

$$\hat{\sigma}^2 = \gamma_0 + 2\sum_{j=1}^{T-1} k\left(\frac{j}{M}\right)\gamma_j \tag{4}$$

where $k(.)$ is the kernel function (e.g., Andrews, 1991), γ_j is the j-th serial covariance of o_i, and M is the bandwidth determined according to the automatic bandwidth selection procedure of Newey – West (1994), which was advocated by Hobijn *et al*. (2004). We used both quadratic spectral (w_{QS}) as well as Bartlett (w_B) kernel weighting schemes. The asymptotic critical values were obtained from the work of Hobijn *et al*. (2004, Table 5).

Let the sample be split into two parts, with sample sizes $T_2 = k_n T_1$. We are interested to test the null of constant unconditional variances, H_0: $\mathrm{E}[\mu_2^{(1)}] = \mathrm{E}[\mu_2^{(2)}]$, where

$$\mu_2^{(1)} = T_1^{-1}\sum_{t=1}^{T_1}\varepsilon_t^2 \tag{5}$$

$$\mu_2^{(2)} = T_2^{-1}\sum_{t=T_1+1}^{T_2}\varepsilon_t^2 \tag{6}$$

The test statistics of Pagan – Schwert (1990) and Loretan – Phillips (1994) are as follows:

$$V_k(d) = d\sqrt{\frac{T_1}{(1+k_n)\upsilon^2}} \qquad (7)$$

where $d = \mu_2^{(1)} - \mu_2^{(2)}$ and υ^2 are the nonparametric estimates of the long-run variance of ε_t^2, estimated in a similar way as in *(4)*. For the daily stock return series, *M* was chosen to be 13, as in previous studies of Pagan – Schwert (1990), Loretan – Phillips (1994), Omran – McKenzie (1999) and Ho – Wan (2002). In addition to the Bartlett kernel weighting scheme, we also employed the quadratic spectral and Parzen kernels. The critical values of *(7)* are determined according to the maximal finite moment exponent *e*. If $e > 4$, under the null, $V_k(d) \to_d N(0, 1)$, which is essentially the Pagan – Schwert (1990) test. Loretan – Phillips (1994) showed that if $e \leq 2$, the test is inconsistent, while for $2 < e \leq 4$, the test is consistent; however, adjusted critical values need to be used, which depend on *e* and *k* ($T \to \infty$, $k_n \to k$). If $2 < e \leq 4$, we used critical values of Omran – McKenzie (1999, Table 1), which were closest to our estimates of the *e* parameter. Similar to previous studies, we considered only three choices of *k*, namely, 0.5, 1, and 1.5. The maximal moment exponent was estimated using the Hill (1975) estimator. The left- and right-tail estimates of *e* are given by the following:

$$e_L(s) = \left(s^{-1}\sum_{j=1}^{s} \ln\left(-\varepsilon_{(j)}\right) - \ln\left(-\varepsilon_{(s+1)}\right) \right)^{-1} \qquad (8)$$

$$e_R(s) = \left(s^{-1}\sum_{j=1}^{s} \ln\left(\varepsilon_{(n-j+1)}\right) - \ln\left(\varepsilon_{(n-s)}\right) \right)^{-1} \qquad (9)$$

where $\varepsilon_{(1)} < \varepsilon_{(2)} < \ldots$ and $s = T^{2/3}(\ln(\ln(T))^{-1}$. It is known that these estimates are asymptotically normal with mean *e* and variance e^2/s.

Sansó *et al*. (2004) proposed two statistics for detecting shifts in the unconditional volatility. The first statistic considers the non-normality of ε_t, and the second statistic also considers the conditional heteroskedasticity. We used the second statistic, denoted as κ_2. The asymptotic distribution of the κ_2 test requires the existence of the fourth moment, which, as will be seen, is not likely in our data. However, the Monte Carlo simulations in Sansó *et al*. (2004) suggest that in finite samples with a non-constant fourth moment, the test has still good size. Therefore, we decided to use this test; however, our results should be interpreted with caution. κ_2 is defined as follows:

$$\kappa_2 = \sup_k \left| T^{-1/2} G_k \right| \tag{10}$$

$$G_k = \hat{\omega}_4^{-1/2} \left(C_k - \frac{k}{T} C_T \right) \tag{11}$$

where $C(k = 0) = 0$ and $C(k) = \sum_{t=1}^{k} \varepsilon_t^2$ for $k = 1,2,...,T$ is the cumulative sum of squares and the fourth moment ω_4 is estimated using nonparametric estimates (as in *(4)*). The critical values for each statistic were obtained from a response surface provided by Sansó *et al*. (2004). The test is applied using the ICSS algorithm (for details, see, Inclán – Tiao, 1994).

3. Results and Discussion

In the large majority of cases, we were able to reject the null hypothesis of a unit-root in the returns of the stock prices in CEE. Similarly, using the KPSS test we were unable to reject the null of stationarity. The evidence therefore allows us to consider stock returns in CEE to be mean stationary. As a consequence, at least asymptotically, our variance analysis should not be confounded by time-varying means of the series. The detailed results from the ADF-GLS and KPSS tests are reported in Appendix 1 and 2.[2]

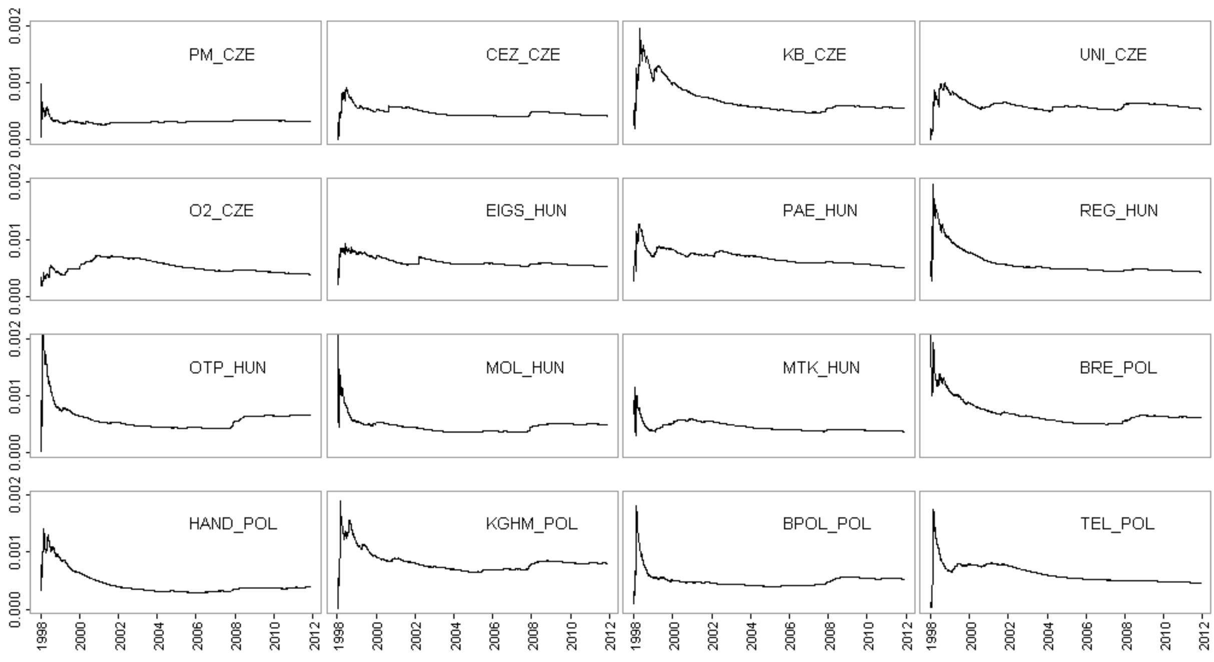

Figure 1: Recursive estimates of daily ε_t unconditional variance

[2] For some series, we found large differences in the number of lags selected by the various lag-selection criteria using the ADF-GLS test. The largest differences can be attributed to the MAIC of Perron – Qu (2007).

In Figure 1, we plotted the recursive estimates of the variance of ε_t over the full sample. The variances appear to converge to some constants signaling covariance stationarity; however, occasional shifts are clearly visible. This result suggests breaks in the unconditional variance or, stated differently, that there are several periods of covariance stationarity. The results from a more formal testing are presented in Appendix 3.

The point estimates of the moment exponent lie within 2 and 4. At significance level $\alpha = 0.10$, the null hypothesis of constant variance cannot be rejected for 4 out of 16 stocks. These stocks are all from the Czech stock market. Three out of four companies belong to the energy and financial sectors, which underwent volatile periods during the last decade; covariance nonstationarity would therefore be expected. Moreover, other companies from these sectors are also present in our sample. For the Polish and Hungarian stock markets, there is strong evidence of covariance nonstationarity.

We have also expected that the hypothesis of constant variances will be rejected mostly for $k = 1.5$, i.e., due to the uncertainty resulting from the financial crisis. In 10 cases, $|V_k(d)|$ was larger for $k = 0.5$ than for $k = 1.5$. Therefore, at least for these tests, one could assume that the break in covariance stationarity occurred mostly at the beginning of the sample period, i.e., from 1 December 1998 to 17 July 2003.

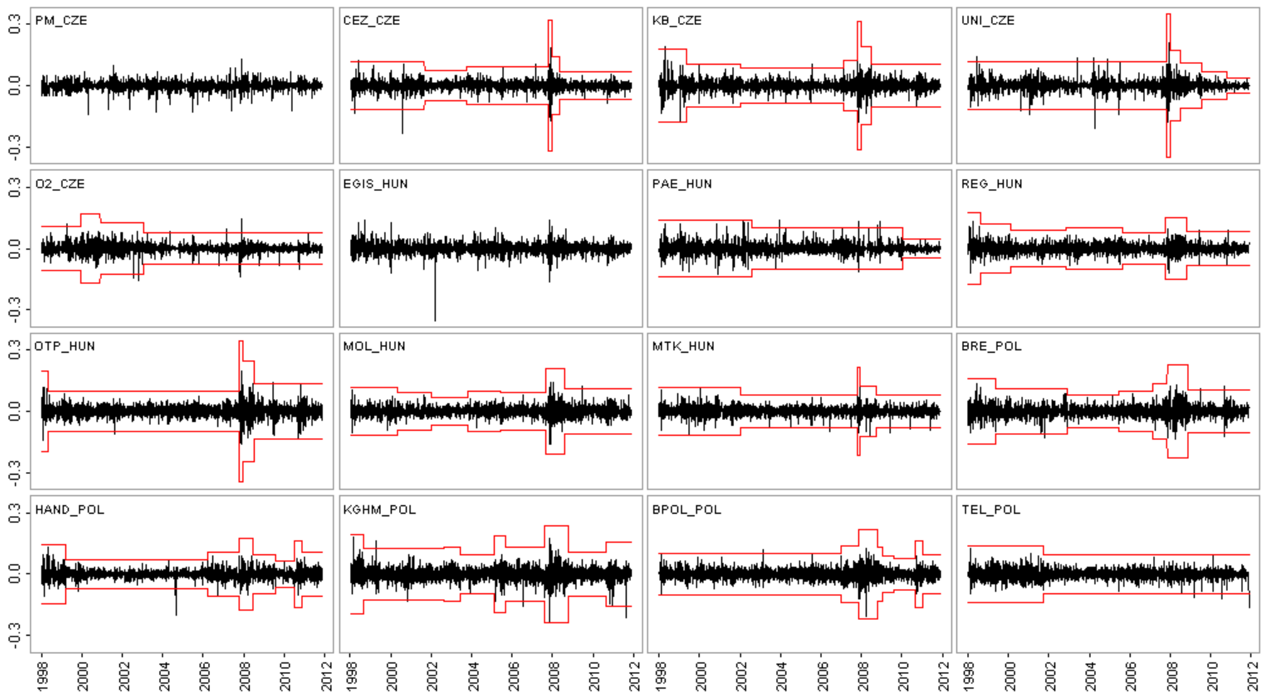

Figure 2: Residuals ε_t and volatility regimes

A natural extension of the covariance stationarity analysis is the identification of possible shifts in the unconditional volatility, which might be responsible for the covariance nonstationarity. We utilized the κ_2 test of Sansó *et al*. (2004) to estimate the possible shifts in the unconditional volatility. Omran – McKenzie (1999) and Ho – Wan (2002) determined the possible breaks in volatility exogenously. Their model assumed that after an increase, the volatility slowly returns to the previous level. Our approach is different. We assume that there might be periods of high/low volatility. The identified breaks are shown in Figure 2.

From Figure 2, it is apparent that more breaks were identified at the end of the sample. This result might be attributed to the recent financial crisis. Another interesting feature of our results that is apparent from Figure 2 is that at the beginning of the sample, the volatility regimes were longer and the volatility was decreasing. Both of these findings are interesting because they suggest that higher volatility might have been the consequence of low liquidity and overall low attractiveness of these stock markets. Therefore, it seems that periods of higher volatility were connected to the degree of development of these stock markets. At the same time, volatility regimes at the end of the period appear to be shorter and more intense. The occurrence of breaks toward the end of our sample also appears to be synchronized, which leads us to the conjecture that a common factor(s) is (are) responsible for volatility shifts in stock returns. We decided to explore this possibility while keeping the analysis straightforward.

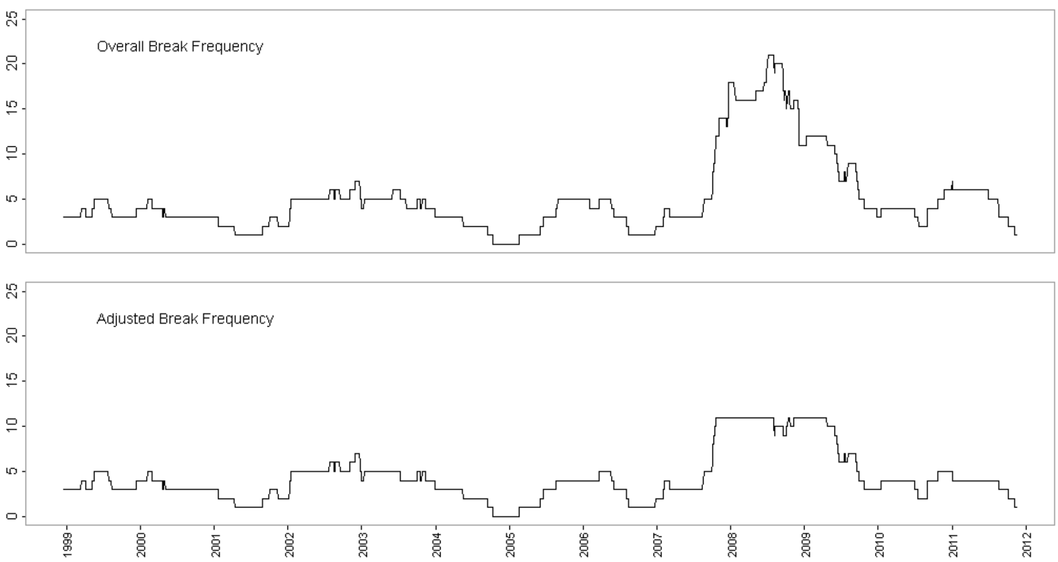

Figure 3: Frequency of breaks, calculated over a fixed rolling window of length 250 days

The upper part of Figure 3 presents the frequency of the volatility breaks calculated over a window of 250 days, which was rolled to the end of the sample. For some stock returns, we identified more breaks than for others. We have therefore calculated the frequency of breaks with the one restriction that for one stock the maximum number of breaks during the 250-day window was 1. This measure is plotted in the lower part of Figure 3.

Both plots in Figure 3 emphasize the fact that the occurrence of breaks across stocks is not random. The occurrence of breaks appears synchronized; therefore, (a) possible common factor(s) might be responsible for these breaks. While this finding is not surprising, it also suggests that firm- or industry-specific factors appear to be of lesser importance.

Conclusion

The goal of this paper was to assess the covariance stationarity of stocks in three CEE stock markets, namely, the Czech, Polish and Hungarian stock market. Using the testing procedure of Pagan – Schwert (1990) and Loretan – Phillips (1994), we conclude that, in general, the assumption of covariance stationarity of stock returns is not warranted for CEE stock markets. To be more specific, we rejected the null of constant variance for at least one k = 0.5, 1.0, 1.5 of 12 stocks in Poland and Hungary but only for one in the Czech Republic. We further investigated the possible reasons for covariance nonstationarity by dating the structural breaks in volatility using the test of Sansó *et al*. (2004). Although these results need to be interpreted with caution (due to the possible nonexistence of the fourth moment in excess returns), they suggest that from approximately 1 December 1998 to 17 July 2003, volatility regimes were longer and volatility was decreasing, whereas during the recent financial crisis, there were more volatility regimes that were much shorter but also much more intense. Furthermore, we found evidence that these shifts in volatility occur within a short period of time, thus providing evidence that covariance stationarity of stock returns in CEE appears to be disturbed by common factors.

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Appendix 1: Unit-root test results (ADF-GLS test)

	$r_{t,PM}$		$r_{t,O2}$		$r_{t,OTP}$		$r_{t,HAND}$	
	statistics	lag	statistics	lag	statistics	lag	statistics	lag
$\tau_{\mu,s}^{GLS}$	-3.529***	29	-1.657*	29	-4.905***	29	-1.818*	29
$\tau_{\mu,m}^{GLS}$	-3.529***	29	-1.657*	29	-4.905***	29	-1.818*	29
$\tau_{\mu,O}^{GLS}$	-8.191***	10	-2.941***	15	-4.905***	29	-3.105***	15
$\tau_{\mu,u}^{GLS}$	-5.671***‡	17	-2.703**‡	17	-7.649**‡	18	-2.853**‡	17
	$r_{t,CEZ}$		$r_{t,EGIS}$		$r_{t,MOL}$		$r_{t,KGHM}$	
	statistics	lag	statistics	lag	statistics	lag	statistics	lag
$\tau_{\mu,s}^{GLS}$	-4.594***	29	-1.359	29	-7.665***	29	-1.221	28
$\tau_{\mu,m}^{GLS}$	-4.594***	29	-1.359	29	-7.979***	26	-1.221	28
$\tau_{\mu,O}^{GLS}$	-4.594***	29	-1.470	27	-27.913***	3	-1.221	28
$\tau_{\mu,u}^{GLS}$	-7.189***‡	17	-2.181**‡	17	-16.469**‡	10	-1.968**‡	17
	$r_{t,KB}$		$r_{t,PAE}$		$r_{t,MTK}$		$r_{t,BPOL}$	
	statistics	lag	statistics	lag	statistics	lag	statistics	lag
$\tau_{\mu,s}^{GLS}$	-1.651	29	-2.645***	28	-5.972***	29	-0.783	29
$\tau_{\mu,m}^{GLS}$	-1.691*	28	-2.645***	28	-6.319***	27	-0.783	29
$\tau_{\mu,O}^{GLS}$	-18.110***	1	-2.645***	28	-5.972***	29	-14.305***	1
$\tau_{\mu,u}^{GLS}$	-2.692**‡	17	-4.050**‡	18	-9.501**‡	17	-1.415	20
	$r_{t,UNI}$		$r_{t,REG}$		$r_{t,BRE}$		$r_{t,TEL}$	
	statistics	lag	statistics	lag	statistics	lag	statistics	lag
$\tau_{\mu,s}^{GLS}$	-9.271***	29	-4.145***	29	-1.401	29	-2.697***	29
$\tau_{\mu,m}^{GLS}$	-9.271***	29	-4.272***	27	-1.401	29	-2.697***	29
$\tau_{\mu,O}^{GLS}$	-9.271***	29	-35.035***	1	-1.401	29	-29.700***	1
$\tau_{\mu,u}^{GLS}$	-26.590***‡	5	-5.508**‡	19	-2.316**‡	19	-4.674**‡	18

Notes: ***, ** and * denote significance at 1%, 5%, and 10%, respectively. Critical values for $\tau_{\mu,s}^{GLS}$ and $\tau_{\mu,m}^{GLS}$ are obtained from Cook – Manning (2004). Critical values for $\tau_{\mu,u}^{GLS}$ are calculated from response surfaces of Cheung – Lai (1995, Table 1). ‡ emphasizes that only critical values for α = 0.05 and 0.10 were known. For $\tau_{\mu,O}^{GLS}$ we used the asymptotical critical values as in Elliott et al. (1996).

Appendix 2: Stationarity test results (KPSS test)

	KPSS	*bw*		*KPSS*	*bw*
$r_{t,PM}$	0.1210	8	$r_{t,OTP}$	0.2368	7
$r_{t,CEZ}$	0.3951*	10	$r_{t,MOL}$	0.1007	5
$r_{t,KB}$	0.2530	5	$r_{t,MTK}$	0.0679	6
$r_{t,UNI}$	0.1242	7	$r_{t,BRE}$	0.0653	1
$r_{t,O2}$	0.0471	3	$r_{t,HAND}$	0.0486	4
$r_{t,EGIS}$	0.1518	10	$r_{t,KGHM}$	0.0686	6
$r_{t,PAE}$	0.2404	6	$r_{t,BPOL}$	0.1821	8
$r_{t,REG}$	0.1427	11	$r_{t,TEL}$	0.0843	10

Notes: The test statistics correspond to the test with long-run variance estimated using a quadratic spectral weighting scheme. The results for the Bartlett weighting scheme are qualitatively identical.

Appendix 3: Results from the covariance stationarity tests

	$V_k(d)$			e			$V_k(d)$			e	
	k = 0.5	k = 1	k = 1.5	lower	upper		k = 0.5	k = 1	k = 1.5	lower	upper
$\varepsilon_{t,PM}$	0.3808	0.1906	-0.0330	2.5686	3.6695	$\varepsilon_{t,OTP}$	2.1639**	3.8722***	4.8240***	2.7913	2.9322
	[3.08E-04]	[3.15E-04]	[3.19E-04]	(0.2427)	(0.3467)		[4.86E-04]	[4.41E-04]	[4.37E-04]	(0.2638)	(0.2771)
	[3.24E-04]	[3.23E-04]	[3.18E-04]				[7.42E-04]	[8.73E-04]	[9.86E-04]		
$\varepsilon_{t,CEZ}$	-1.0759	-0.4176	0.0400	2.9161	3.0107	$\varepsilon_{t,MOL}$	1.5892*	3.1704***	3.7705***	3.3885	3.3755
	[4.84E-04]	[4.35E-04]	[4.15E-04]	(0.2755)	(0.2845)		[4.07E-04]	[3.70E-04]	[3.73E-04]	(0.3216)	(0.3204)
	[3.82E-04]	[3.98E-04]	[4.18E-04]				[5.42E-04]	[6.25E-04]	[6.83E-04]		
$\varepsilon_{t,KB}$	-1.5397	0.0507	1.4417	2.6663	2.8356	$\varepsilon_{t,MTK}$	-4.3918***	-2.2467**	-1.4552	2.9497	3.2043
	[6.51E-04]	[5.48E-04]	[4.95E-04]	(0.2519)	(0.2679)		[5.12E-04]	[4.23E-04]	[3.99E-04]	(0.2787)	(0.3028)
	[4.99E-04]	[5.52E-04]	[6.32E-04]				[3.03E-04]	[3.23E-04]	[3.33E-04]		
$\varepsilon_{t,UNI}$	-0.6478	-0.9349	-0.2480	2.8556	2.7081	$\varepsilon_{t,BRE}$	-0.4872	1.7327**	2.8253***	3.0051	3.4467
	[5.92E-04]	[5.93E-04]	[5.54E-04]	(0.2710)	(0.2570)		[6.37E-04]	[5.38E-04]	[5.15E-04]	(0.2840)	(0.3257)
	[5.19E-04]	[4.93E-04]	[5.27E-04]				[5.95E-04]	[6.79E-04]	[7.49E-04]		
$\varepsilon_{t,O2}$	-6.8663***	-5.0858***	-3.6841***	3.0787	3.0111	$\varepsilon_{t,HAND}$	0.5194	2.4034***	3.9516***	2.7558	2.9446
	[6.70E-04]	[5.34E-04]	[4.72E-04]	(0.2909)	(0.2845)		[3.65E-04]	[3.17E-04]	[2.94E-04]	(0.2604)	(0.2782)
	[2.40E-04]	[2.33E-04]	[2.50E-04]				[3.96E-04]	[4.54E-04]	[5.23E-04]		
$\varepsilon_{t,EGIS}$	-1.9724*	-0.9765	-1.1643	3.7308	3.1403	$\varepsilon_{t,KGHM}$	0.7632	2.8587***	2.4735***	2.8328	3.3731
	[6.48E-04]	[5.63E-04]	[5.62E-04]	(0.3525)	(0.2967)		[7.48E-04]	[6.51E-04]	[6.97E-04]	(0.2677)	(0.3187)
	[4.52E-04]	[4.72E-04]	[4.51E-04]				[8.36E-04]	[9.62E-04]	[9.71E-04]		
$\varepsilon_{t,PAE}$	-5.6148***	-4.3463***	-3.4235***	2.9235	2.8353	$\varepsilon_{t,BPOL}$	1.9447**	3.5815***	4.0141***	3.3773	3.3183
	[7.84E-04]	[6.54E-04]	[5.97E-04]	(0.2762)	(0.2679)		[4.34E-04]	[4.04E-04]	[4.15E-04]	(0.3191)	(0.3136)
	[3.52E-04]	[3.38E-04]	[3.44E-04]				[5.80E-04]	[6.58E-04]	[7.05E-04]		
$\varepsilon_{t,REG}$	-2.7375***	-2.3533**	-1.9741**	3.6259	3.4670	$\varepsilon_{t,TEL}$	-6.7629***	-3.8138***	-3.1233***	3.8468	3.7897
	[5.18E-04]	[4.82E-04]	[4.65E-04]	(0.3426)	(0.3276)		[7.01E-04]	[5.59E-04]	[5.27E-04]	(0.3635)	(0.3581)
	[3.80E-04]	[3.71E-04]	[3.69E-04]				[3.46E-04]	[3.70E-04]	[3.69E-04]		

Notes: ***, ** *and* * *denote significance at 1%, 5%, and 10%, respectively. Unconditional volatilities are in* [] *and standard deviations of e in* (). *Using the quadratic spectral or Parzen weighting schemes resulted in very similar results; therefore, only results for the standard Bartlett kernel weighting scheme are reported.*